# Manifesto for Science Communication as Collective Intelligence

## RED GROUP SECTION:

## Why Collective Intelligence?

### The landscape of SciComm today (and the problems for science)

Many of the most pressing challenges that societies face today-- from climate change to a global pandemic--require large-scale, collective decisions informed by the best available evidence. It is only when public beliefs are built on reliable knowledge, rather than poorly informed opinions, that we can successfully address these challenges. However, in many situations in which evidence is in conflict with political or commercial interests, public discourse is polluted by organized efforts to misinform, sow public confusion, or advance conspiracy theories (APCO Worldwide, 2021; Graham et al., 2020). Those efforts can severely threaten informed debate among citizens and policy makers. For example, there is little doubt that organized climate denial has delayed mitigative policy action (Lewandowsky, 2020, 2021). The coronavirus pandemic has both exacerbated and exposed many of the dangers of science-related misinformation. It is now known that coordinated campaigns kick-started the hoax that 5G Internet causes the coronavirus (Graham et al., 2020), and that at least one libertarian think tank

with a history of climate denial has funded opposition to social distancing measures to control the pandemic (Lewandowsky, 2021; Bragman & Kotch, 2021). Anti-vaccination misinformation is increasingly embedded within broader conspiracy narratives such as 'The Great Reset', pushing the idea that vaccinations are part of a plan to exert population control (APCO Worldwide, 2021).

From a policy and public health perspective, this means that effective public health measures have become increasingly contested (Vériter et al., 2020), preventing some citizens from implementing scientifically-grounded health measures (Posetti & Bontcheva, 2020; plus include original publications). Furthermore, we now know that the COVID-19 pandemic has been exploited by state-sponsored media, and far-right networks that are the key drivers of online misinformation by means of orchestrated, strategic information operations (ISD, 2020; Starbird et al., 2019) In other words, we now know that disinformation often arises from well-organized collaborative work–not just in the context of COVID (Starbird et al., 2019) but also in the context of climate change (Lewandowsky, 2021b), tobacco control, and numerous other instances in which scientific evidence threatened vested interests (e.g., Oreskes & Conway, 2010).

Here, we argue that science communication needs to be collaborative as well. This manifesto lays the foundation for a collective intelligence view on science communication that harnesses the collective knowledge and

expertise of large numbers of scientists worldwide, thereby providing high-quality information, delivering more effective countermeasures to the spread of mis- and disinformation, and ultimately contributing to an informed citizenry.

A collective intelligence approach to science communication provides a remedy to the perils and pitfalls of the traditional “one-person reporting” model. One pitfall of communication by single individuals is that opponents can pursue the “Serengeti strategy” (Mann, 2015), which refers to the idea that in the same way that lions in the Serengeti seek out individual zebras that are left behind or stray from the herd, vested interests and political operatives faced with adverse scientific evidence often target individual scientists rather than take on an entire scientific field at once. It is for this reason that individual prominent scientists often become a focus of attacks by contrarians. Perhaps the most prominent recent example involves Dr Anthony Fauci, the Chief Medical Advisor to the President of the United States, who has been relentlessly and personally attacked by political operatives who objected to pandemic-control measures (Korecki & Owermohle, 2021).

Another pitfall of individuals communicating on their own is that lone voices may distort perceptions of a scientific consensus. For too long, media coverage of scientific evidence on topics such as climate change or vaccinations has been “balanced”, lending equal weight to a position that is

supported by overwhelming evidence and by the majority of scientists, and a position that is supported by little or no evidence. Although mainstream media has largely moved beyond false balance in recent years, (Bruggemann & Engesser, 2017), this strategy has succeeded in maintaining public uncertainty about the scientific consensus around anthropogenic climate change or the vaccine-autism myth (Dixon & Clarke, 2012; Koehler, 2016).

Another danger in single individuals communicating science lies in them (intentionally or not) misrepresenting an actual consensus, or being perceived as misrepresenting a consensus. A collective intelligence approach to science communication, in contrast, weights information by the strength of evidence: Rather than perceiving evidence as just “one more piece of information” in the debate, evidence that is supported by the consensus of the collective can be seen as decisive (e.g., Imundo & Rapp, 2021). A collective intelligence approach to science communication therefore delivers evidence that can reliably inform the actions of citizens and governments alike.

There is ample evidence that collective communication, embodied in messages that reflect a scientific consensus, can reliably shift the public’s attitudes and strengthen calls for policy action in climate change (van der Linden et al., 2019), COVID-19 mitigation (Kerr & van der Linden, 2021) and vaccinations (van der Linden et al., 2015). Communicating a consensus can

be effective even across partisan lines. It has been shown that underscoring the consensus on climate change can be particularly effective for conservative participants, who tend to be predisposed towards rejecting scientific evidence for climate change (Lewandowsky et al., 2013).

[transition to the next subsection]

**What is “collective intelligence”?**

But what exactly is "collective intelligence" (CI) and how might it look like in the domain of science communication? In its broadest form, CI can be seen as the process of collaborative problem solving and collective decision making, with the aim to produce outputs that are better than the sum of its parts. Before unpacking the general concept of CI any further, it is important to realize that research on CI spans a wide spectrum of research fields, such as psychology, biology, management, economics, sociology, political science, and computer science (Malone & Bernstein, 2015). Furthermore, applications of CI range across diverse domains, such as crowdsourcing medical diagnostics (e.g., The Human Diagnosis Project), crowdsourcing geopolitical forecasting (e.g. the Good Judgment Project and its "Superforcasters"), citizen science in astronomy and beyond (e.g., Zooniverse), collaborative writing and editing on wikipedia, or collective deliberation in political processes (e.g., deliberative democracy [what's a good example + link?]).

Examples of collective intelligence in the context of science communication can be drawn from various sources and disciplines (Suran et al. 2020). An attempt is made to present tangible, balanced, and accessible collective intelligence examples from the science communication area that help inform, educate, engage, and network the public and use different channels to communicate their important messages. These systems and platforms enable, for instance, problem-solving, decision-making, and knowledge-sharing. The following box (Box 1) presents recent examples on guidebook creation, information dissemination to assist policy-development, and environmental education and solution-generation. These are only a few of the important issues science communication brings to the public by leveraging the strengths of collective intelligence. These examples illustrate the collaborative nature of science communication and how collective intelligence can be used to highlight the positive power of scientific knowledge, people working together, and engaging the public.

| **CI Platform** | **Description** |
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| **The Debunking Handbook** | This written document and guide is a prime example of a SciComm collective intelligence effort. Since the scientific knowledge about debunking has noticeably evolved over |

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| **2020** | the last ten years, this collective project updated the first edition of the Handbook. It is also an effort to unify the knowledge and convey scientific consensus about the academic field of debunking to its audience. The Handbook was designed using a preregistered approach, as such preregistering the methodology and intended completion schedule. The collective production of this document was informed by research on the process of consensus formation in a medical context (e.g., Rosenfeld, Nnacheta, & Corrigan, 2015). In addition, the authors utilized precedents from psychology to enrich this SciComm document. As a matter of fact, the handbook creation process, as far as the author selection, preregistered process of document production, scope definition, methodology design, and result presentation are concerned, involves steps that leverage a collective intelligence process. |
| | Note:<br><br>Lewandowsky, S., Cook, J., & Ecker, U.K.H. (2020). Under the Hood of The Debunking Handbook 2020: A consensus-based handbook of recommendations for correcting or |

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| | preventing misinformation. [Working Paper, document creation process].<br><br>Rosenfeld, R. M., Nnacheta, L. C., & Corrigan, M. D. (2015). Clinical consensus statement development manual. *Otolaryngology—Head and Neck Surgery*, 153, S1-S14. |
| **indie_SAGE** | The public policy channel for this independent scientific advisory panel employs multiple outlets to communicate, such as reports, weekly briefings, and events to inform the public and aid policy makers. Indie_SAGE, also known as The Independent Scientific Advisory Group for Emergencies, is a group of scientists not connected to the government which works collectively to provide impartial scientific advice to the UK government and policy makers about the current Corona pandemic. This advice is aimed at reducing deaths and the strain on the UK health system as well as helping to manage the pandemic response. The group wants to educate the public about this crisis. Indie_SAGE sees transparency as one important key factor to be successful in the fight against the pandemic and support the UK leadership and decision-making. |

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| | Note:<br><br>https://www.independentsage.org/<br><br>Landler, M., & Castle, S. (23 April 2020). “The secretive group guiding the UK on Coronavirus.” *The New York Times*. https://www.nytimes.com/2020/04/23/world/europe/uk-coronavirus-sage-secret.html<br><br>“Revealed: Cummings is on secret scientific advisory group for Covid-19. *The* Guardian. 24 April 2020. https://www.theguardian.com/world/2020/apr/24/revealed-dominic-cummings-on-secret-scientific-advisory-group-for-covid-19. |
| **openIDEO** | This digital platform is an electronic management system that mimics a collaborative incubator for creating solutions to current problems. openIDEO is a creation and innovation platform. This space focuses on environmental, ecological, and climate issues and challenges and on how to solve them. This maker-space (see also Stanford d.School) enables its users to, collaboratively, work on solutions for contemporary problems. Through this |

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| | process, openIDEO also aims to encourage community involvement and societal change. Different parties can get involved in these friendly but somewhat competitive projects, such as experts, sponsors of particular projects, and outside consultants. |
| | Note:<br><br>https://www.openideo.com/<br><br>Suran, S., Pattanaik, V., & Draheim. D. (2020). Frameworks for Collective Intelligence: A Systematic Literature Review. *ACM Computing Survey*. 53, 1, Article 14 (February 2020), 36 pages. https://doi.org/10.1145/3368986 |
| **Wikipedia** | Wikipedia is an online free-content encyclopedia supported by the Wikipedia Foundation, which communicates a wide range of topics related to scientific knowledge. Wikipedia's content is produced collaboratively by anonymous volunteers and is freely editable except in limited cases to prevent disruption or vandalism. The fundamental principles of the project are summarized in its five pillars: encyclopedic knowledge, neutrality, openness, civility, and adaptability. Because everyone can help improve it, it has |

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| | become more comprehensive than any other encyclopedia and its contributors work on improving their quality, removing and repairing misinformation and other errors. Over time, articles tend to become more comprehensive and balanced. Wikipedia has grown into the world's largest reference website, with more than fifty-eight million articles in more than 300 languages, 127,165 active contributors, and 1.7 billion visitors monthly. |
| | https://en.wikipedia.org/<br><br>Livingstone, R. (2016). Models for Understanding Collective Intelligence on Wikipedia. *Social Science Computer Review, 34*(4), 497-508. https://doi.org/10.1177/0894439315591136 |
| **COVID-19 Vaccine Communication Wiki and Handbook** | The COVID-19 Vaccine Communication Wiki and Handbook project is run by the SciBeh research group. This wiki constitutes a comprehensive online guide to offer practical tips based on the very latest evidence to talk reliably about vaccination and its associated myths and fears. The interdisciplinary team includes experts in vaccine psychology, education and virology who volunteer to |

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| | produce a living document, which will continue to evolve through as the vaccine rollout gains pace. The key contents of the wiki have been edited as a handbook and translated into 12 languages, including summaries for policy-makers. |
| | https://hackmd.io/@scibehC19vax/home |

Research on CI has produced several important and general theoretical insights and empirical findings that should inform the design of any CI-system (e.g., cognitive diversity among the members of a crowd are usually beneficial for CI). On the other hand, there are several key aspects of a CI system whose effect will depend on the particular setting; for example, social influence among the members of a collective can benefit CI (EXAMPLE) or harm CI (EXAMPLE). As a consequence, there is no single, generic, off-the-shelf, one-size-fits-all configuration that can be directly applied to any use case. Rather, each use case needs its own, "bespoke" configuration of

components and processes, informed by both theoretical and empirical insights and what is known about the application at hand.

So what are those building blocks for configuring a CI system? The breadth of perspectives, domains, and applications has led to different proposals about what exactly CI is, how to ensure its success and what success actually means in the first place. In the context of science communication as a collective intelligence enterprise, we believe it is useful to start out thinking about CI as a "form of universally distributed intelligence, constantly enhanced, coordinated in real time, and resulting in the effective mobilization of skills" (Levy, 1997), embedded in and facilitated by suitable socio-technological systems (e.g., wikis, forums, deliberation platforms). Figure 1 summarizes the key components and processes of collective intelligence systems from an Information and Communications Technology perspective (adapted from Suran et al., 2020). Those building blocks revolve around four key questions about any CI-system, namely, "who?" (the "staff") is doing "what?" (goal), exactly "how?" (process) and "why?" (motivation). As an example for the process, interactions between crowd members can be dependent (i.e., everybody can see what others are doing) or independent (i.e., everybody works independently, at least initially). As alluded to further above, which configuration is preferable will depend on the specifics of the task.

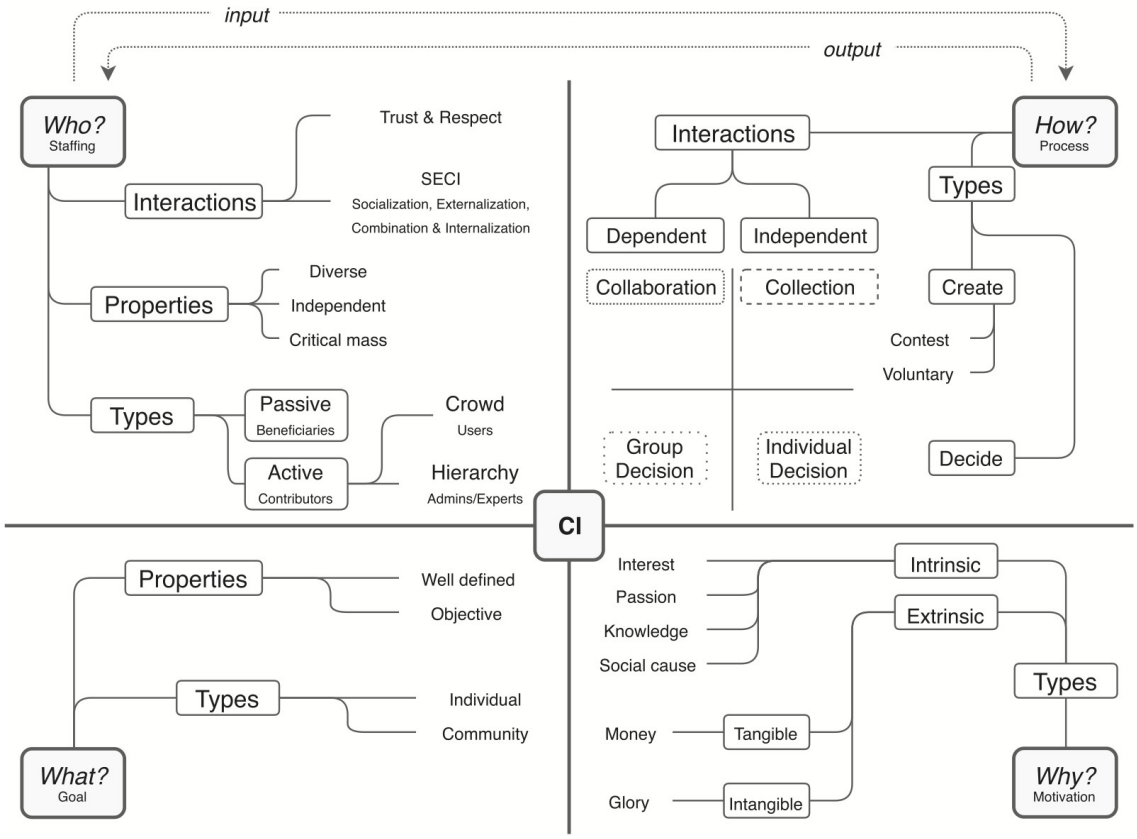


Fig. 1. Generic model for collective intelligence systems.

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At this point, you might wonder, what is *not* CI? Arguably, there is no human activity that is not, in one way or another, informed or influenced by what other humans have done before (i.e., cumulative culture) or are currently doing (e.g., on social media, on the streets, or in organizations). In the context of science communication, we think it is useful to focus on those forms of collective behavior that have been intentionally and deliberately designed to produce successful and tangible "artefacts" through

collaborative problem solving and collective decision making ("deliberate CI"). In this view, wikipedia is a form of deliberate CI because the collective creates and refines wikipedia articles on particular topics. In contrast, the collective behavior of pedestrians is not a form of deliberate CI, notwithstanding how intelligent the emergent behavior might often be or how intelligent the urban planning supporting it might have been. Science communication, in one way or another, needs tangible artefacts to communicate information and to engage with the public (e.g., data visualizations) .

[interim summary and advanced organizer, foreshadowing key topics and questions that will be spelled out in more detail in the remainder the text]

ORANGE GROUP SECTION:

**SciComm as CI: What is required?**

So what is required in order to achieve a novel, collective approach to science communication? In replacing ‘one person reporting’ with a collective, we need to fundamentally consider the processes and axioms underlying the aggregation of knowledge. How can information from diverse sources be integrated into a coherent and representative whole? How can dissent, if it exists, be incorporated? And how can politically-motivated opinion be filtered out from evidence-based views?

One of the earliest established principles of knowledge aggregation is Condorcet's Jury Theorem. The theorem tells us that when judgments about guilt or innocence are aggregated across jurors who are (more or less) independent, and when the probability of each juror being "correct" is at least 50%, then the majority will converge on the correct outcome as more individuals are added to the vote. It is therefore epistemically entirely appropriate to rely on an expert consensus, ascertained by averaging or voting (REFS), as a strong signal of knowledge.

However, in rapidly-emerging crisis situations such as the COVID-19 pandemic, which are characterised by high uncertainty, there will be disagreement among experts. In such cases, it may not be appropriate to communicate single, aggregate conclusions by a field; rather it is the ongoing scientific process and attendant debate itself that needs to be communicated. However, care must be taken to calibrate the prominence that is given to various positions based on the strength of the evidence on which they rest.

In the pandemic, online social media platforms such as Twitter or Reddit have helped serve this function, but they are far from ideal for nuanced and respectful communication. On the contrary, social media is notorious for favouring outrage over evidence-based information and it is particularly

beholden to highly-active extreme voices that can significantly distort users' perceptions of the opinion landscape.

New tools that enable scientists to foreground ideas, evidence, and arguments -as opposed to people- seem desirable in order to minimise the risks of polarisation, entrenchment, and degeneration of the discourse. We see scope for novel machine learning and AI tools for visualising and aggregating discourse in to cumulative formats such as argument maps (REFS) that would allow all interested parties to evaluate the evidence, surface underlying limitations, presumptions and biases, as well as help identify holes and weaknesses in the evidential base.

At the same time as investing in novel tools, we also need to reconsider the incentive structure for scientists. As many formal results in judgment aggregation (REFS) and problem solving (REFS) attest, collective intelligence requires epistemic diversity: a scientific "consensus" is valuable and will emerge as understanding of a problem increases. However, consensus formation must not be hasty, but rather genuinely reflect the breadth of viewpoints that both different disciplinary perspectives and life experiences can bring.

This requires career-related incentives for public communication across the career spectrum (from early career researcher to senior academic). Yet at

present, science still struggles to recognise, let alone quantify scientific contributions that are NOT papers. Moreover, these as yet to form incentives must foster listening to, engaging with, platforming, or amplifying others' ideas as well as a willingness to (publicly) self-correct: science communication must be perceived as more than an opportunity to promote one's own favourite scientific opinion, or even worse, unacknowledged mix of politics and science.

Work is required to help devise incentive structures that would foster constructive, respectful and collaborative communication between scientists and given the bi-directional relationship between those incentives, social norms and guidelines must arguably be developed in conjunction with thinking about the medium or tools in which communication takes place. Finally, in all of this, scientists must consider closely how their discourse is perceived and used by others, whether these be policy makers or the general public.

GREEN GROUP SECTION:

## Ways to evaluate evidence strength and consensus

### Evaluating strength and reliability

Scientific communication should not project a distorted image of scientific inquiry, something that often takes place following certain political and

mediatic communication styles. This is particularly important with respect to two issues: scientific methodologies and consensus. On one hand, beyond the usual oversimplifications of school textbooks, there is a wide variety of scientific methods, so scientific research constitutes a complex iterative process in which methodological plurality plays a relevant role. On the other hand, science should not be interpreted as an "all-or-nothing" process in which hypotheses are completely refuted or completely supported. Instead, uncertainty and open deliberation are also integral to scientific confirmation and, therefore, should also be highlighted when communicating results. Concerns or hopes that communicating uncertainty weakens scientific evidence or strengthens it are not supported: Acknowledging uncertainties has neither a positive nor a negative impact on people’s trust or confidence in scientific evidence (van der Bles et al., 2019). For example, health advice issued to reduce the spread of Covid-19 was cross-culturally perceived as equally trustworthy when it was communicated as “effective” or “potentially effective” (Janssen et al., 2021; Zarzeczna et al., 2021). Overall, uncertainty should be openly communicated, but alongside the quality of the evidence (if applicable). Uncertainties can be supplemented with examples of what is currently done to reduce them, which will also allow people to get a better understanding of how knowledge is generated in science (for guidelines, see Blastland et al., 2020; van der Bles et al., 2019).

One of the main sources of bias in science communication lies in poor standards of evidence assessment. For this reason, we defend the establishment of thresholds, both for the quality of the available evidence (e.g., level 1, 2, etc.) and the existing level of agreement among recognized experts. It is a serious problem that studies with methodological limitations, manuscripts that have not yet passed peer review (e.g., pre-prints), data with minuscule effect sizes that are not clearly communicated as such, and isolated studies are being presented to the public as confirmed scientific facts. From our point of view, these practices tend to overvalue flashy, extravagant or politically exploitable studies, leaving aside the complex nuances and levels of uncertainty that characterize scientific inquiry. Scientific communication, here understood as a form of collective intelligence, should develop a shared consciousness of scientific method. This means, among other things, expanding the initiatives framed within the Open Science Movement, thus bringing transparency strategies from the scientific community to the rest of society. We believe that methodological limitations, controversial hypotheses and uncertainty should also be presented to the public. Paternalistic and partisan attitudes only give rise to distorted forms of scientific literacy, which is counterproductive for public deliberation.

When looking at the communication styles employed by scientists and successful communicators online, a difference emerges. Compared to

scientific communication, viral content tends to score high in emotional content, it is characterized by simplicity of the message communicated and is often experiential (Tellis et al., 2019). An effective scientific communication strategy must thus be able to engage the public while at the same time communicate the key scientific facts. Scientific facts are often difficult to communicate in a simple and relatable manner. Current scientific communication often relies on rational arguments and exposure of cold facts, and therefore assumes that the audience will be willing and capable of engaging in analytic thinking. A communication style that relies on high level processing (System 2) in this way risks missing out the fact that people often rely on more automatic forms of information processing (Kahneman, 2011). These forms of information processing are often rapid, low effort and more emotional than System 2. Employing scientific communication strategies that rely on System 1 processing as well as System 2 processing is a first step to create effective messages that can compete with viral content online and decreasing attention span of online content consumers (Lorenz-Spreen et al., 2019). Additionally, reporting effect sizes that can be communicated as percentages (e.g., Common Language Effect Size, Cohen's U3) results in people perceiving findings to be more informative (Hanel & Mehler, 2019).

When researchers design, execute, and write-up studies, there is not only a risk for honest mistakes but also for systematic biases, for example because of researchers' beliefs or the incentive system of their field. For example,

some researchers, especially in the ‘soft sciences’ (e.g., psychology, sociology) focus on findings that are statistically significant while disregarding often the non-significant ones and even engage in questionable research practices to get their findings statistically significant and subsequently more easily published (Fanelli, 2010; John et al., 2012). These biases lead to an overestimation of effect sizes and in low replication rates, which reduces public trust in science (Hendriks et al., 2020). Another type of biases are those based on personal beliefs of researchers. For example, scientists, especially those in the social sciences, tend to be overwhelmingly left-leaning in their political attitudes (Duarte et al., 2015). This might lead to biased research questions such as a focus on biases among conservatives rather than liberals, which could undermine trust in scientists especially among conservatives. Thus, researchers can unknowingly add their biases to any (meta-analytic) conclusions. Reducing these biases through changing the scientific incentive system (cf. Nosek et al., 2012) and making academia more diverse also in terms of political ideology can decrease potential detrimental effects of researchers being humans.

## Scicomm as CI should enable evaluation of consensus

Online platforms can help scientists rapidly share knowledge, discuss evidence and reach a consensus. However, more effort is needed to produce accurate scientific synthesis of scientific data. This could be achieved via

improving statistical packages for meta-analysis. Various methods have been devised to quickly aggregate information from a number of stakeholders. Some date back to the pre-Internet era, e.g. the Delphi Method (Dalkey & Helmer, 1963) is a structured interaction between subject experts where independent expert opinion elicitation methods are alternated with opinion aggregation and inter-expert influence to facilitate the process of information aggregation and consensus reaching. With the rise in internet technologies, several digital platforms have been created with the objective of rapid information aggregation and consensus building. Tools like Polis, PSi, Loomio, Consul and Decidim provide comprehensive packages for debating, proposing and voting on initiatives, giving feedback on textual and numerical data, such as legislation and participating in budget allocation. Although several of these platforms are designed within the space of civic participation, their redeployment within scicomm is feasible.

Decision making processes at the individual level are often modeled as evidence accumulation processes (Ratcliff & McKoon, 2008; Bogacz et al., 2006). In these processes, an evidence summary variable is accumulated synthesizing the difference between evidence in favor and evidence against a given binary decision. These models have been extremely successful in accurately predicting behaviors related to the decision process, such as error rates, reaction times, and confidence judgments. Expansion of these models can accommodate decisions made under weak signals or high uncertainty.

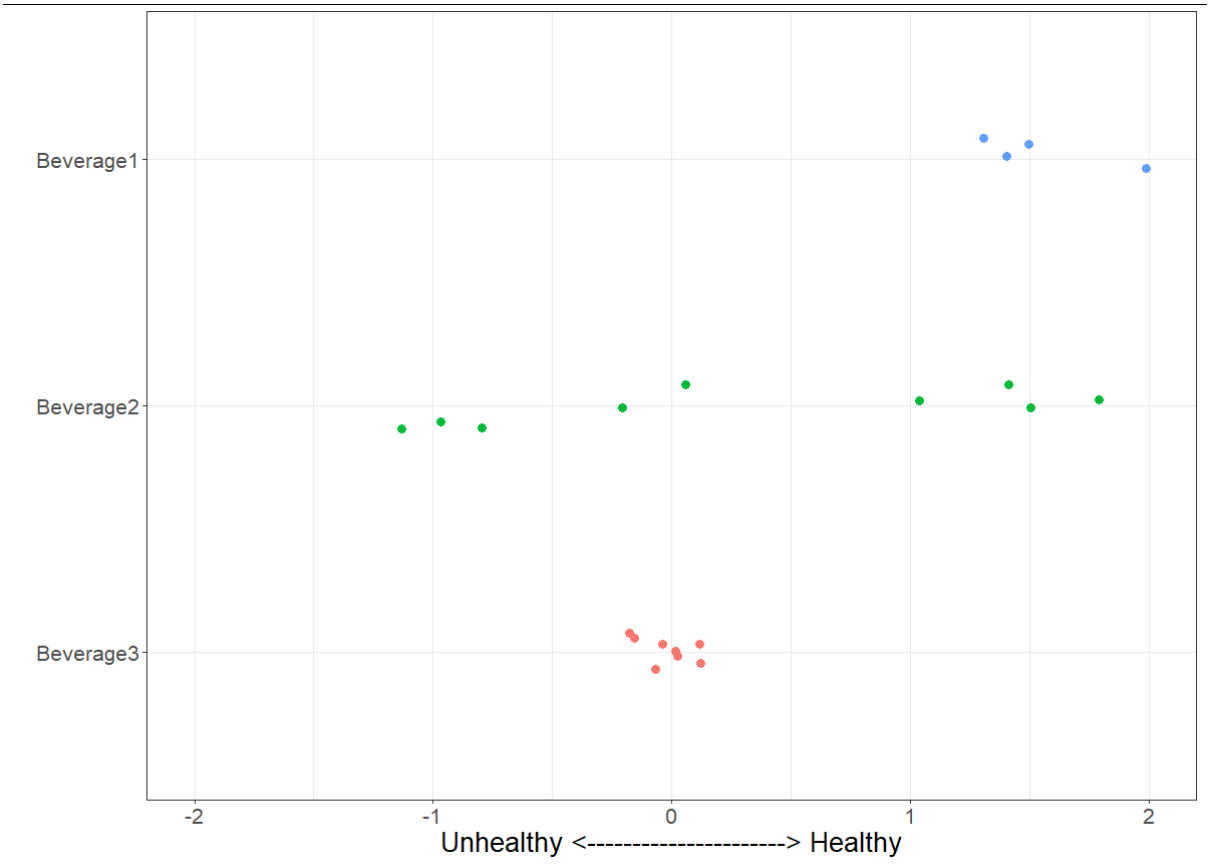
Similar accumulation models could in theory be designed to support decision making around policies that require the careful integration of disparate scientific evidence. Such a “scientific accumulation machine” could be designed to represent the global state of scientific evidence over time. As scientists collect more data and produce more evidence in support or against specific policies, the global state variable could represent a drift diffusion processes that indicates the amount of evidence and confidence of the scientific community and aid scientists make specific policy recommendations.

Visualizing the results from many studies together rather than providing an overall meta-analytically derived effect size is important for several reasons (cf. also Weissgerber et al., 2015). First, visualizations tell us how much agreement there is between studies: Have all studies found something similar or do the findings differ across studies? Second, visualizations tell us whether the findings go all in the same direction: Is X beneficial or detrimental? Third, visualizations tell us about the strength of an effect: Is X only a bit beneficial (or detrimental), substantially, or massively? Fourth, visualizations can tell us how much evidence is available yet. Figure 1 displays a possible way to visualize the effect of multiple studies. In the hypothetical example, the effects of three beverages on our health are displayed. Beverage 1 seems to have a strong positive effect and findings are homogenous across studies. On the flip side, only four studies have

investigated it. The results for beverage 3 are similar except that it does not have much of an effect on our health. Thus, scientific consensus is high for beverages 1 and 3. In contrast, consensus for beverage 2 is low: The effects of studies that investigate beverage 2 show substantial variability. Whereas some studies found that beverage 2 is unhealthy, others found it to be healthy, possibly due to some moderators (e.g., sample size characteristics).

**Figure 1**

*Effects of different beverages on health (simulated data)*



Scicomm as CI should also verify sources of information. With the emergence of pre-print journals and predatory ‘academic’ journals, it is becoming extremely difficult to cope with the rapid pace of scientific production. To add to this quagmire, some of these non peer-reviewed papers get cited either in other academic journals or by the mass media (Fleerackers et al., 2021), which can only further complicate the issue (Miller, 2021). As a result, verifying information must be an ongoing collective process done by experts in the field to evaluate and re-evaluate peer reviewed publications based on scientific consensus—for instance, systems to provide comments on published research. Big data analysis offers tremendous opportunities to find answers to many pressing questions about our world today like climate change, cancer treatments, and pandemics. Yet, large datasets are hard to manually process, and researchers need more financial and administrative support from their institutions to access data, super computers and/or get specialized technical assistance, which are often non-existent for them in many countries especially in the Global South. In terms of misinformation and disinformation, researchers and social media companies need to keep developing advanced AI techniques to sift through large datasets, identify misleading content, and flagging it to other users especially on social media. This, however, cannot be implemented without close collaboration with social media companies that store and control the data and its flow.

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## Design principles to consider in science communication

### Use of narratives

A key consideration in effective communication is the need to connect with audiences. In communicating scientific information, narratives which offer an experiential component may be more effective than facts and figures. While presenting statistical evidence and facts may be useful for improving attitudes towards science and beliefs in line with it, a story-like narrative involving characters and a plot may have a greater influence on behaviour (Zebregs et al., 2014), particularly where the behaviour is health-related or involves potentially severe consequences (Freling et al., 2020). Such narratives may evoke affective responses necessary for eliciting behavioural outcomes as individuals experience the narratives as real events (Green & Brock, 2000; Kopfman et al., 1998). It should therefore be noted that presenting information using as fact-check statements (e.g., “This information has been disputed”) may be largely ineffective as this approach may not tie to beliefs related to personal values, thus not eliciting an emotional response (Oeldorf-Hirsch et al., 2020; Walter et al., 2019). As such, effective science communication, while needing to present evidence, must contain a human element.

**Use of graphics**

In addition to the use of narratives, graphically presenting information may be especially useful for communicating statistical evidence and facts. These graphical representations should take into consideration human elements related to cognition, memory, and attentional processes to create images. This may include using contrasting visual elements to capture one's attention (Harold et al., 2016), arrows to direct focus (Hommel et al., 2001), and reducing visual clutter (Neider & Zelinsky, 2011). Additionally, text can be used in graphics to support understanding and direct inference-making (Harold et al., 2016).

**Communicating risk**

When communicating risks using numbers, however, communicators should choose the appropriate numerical format carefully. For instance, when making statements about simple non-comparative risks (e.g., the risk of a medical procedure) then 1-in-X ratios (e.g., 1 in 10) should be avoided. These are known to increase the perceived probability of the negative events and other formats, such as 10 in 100, are preferred (e.g., Pighin et al, 2011, Sirota & Juanchich, 2019, Sirota et al, 2018). Absolute risks should also be used instead of relative risks, for example, (e.g., an increase in risk from 1 in 100,000 per year to 2 in 100,000 per year, not a ‘doubling’ of risk or a ‘100% increase’ in risk). Such considerations enable scientific information to be communicated in an accessible way.

**Use of simple language**

Several research findings indicate that using simpler language for science communication is best (Martínez & Mammola, 2021). A recent study even showed that specialized terminology reduces the number of citations of scientific papers (Martínez & Mammola, 2021). In an era of interdisciplinarity, the use of jargon may hinder effective communication among scientists that do not share a common scientific background (Martínez & Mammola, 2021). Keeping the language and sentence structure simple and reducing the amount of jargon, makes it easier for professionals from various backgrounds to participate in scientific discourse. It also enables people from different backgrounds to communicate with each other effectively.

**The need for shared language**

In order to effectively talk with each other as well as the public we are in need of a shared language. This not only means that science as collective intelligence needs to agree on one language across different countries, we are also in need of a shared language between disciplines. Whether it is psychology, physics or history, the most diverse disciplines must find a way to effectively communicate with each other. This is a requirement in order to enable science as collective intelligence in all areas and across different research fields.

**‘Evidence’ versus ‘proof’**

Most languages translate the word “evidence'' as “proof” which implies no error in inferences but in English implies possibility of false evidence. Evidence in the English language is a broad term and in the widest sense can only mean something like "sign" or "indication of something". The term evidence cannot always be rendered to “proof” no matter the context. Such translation problems as presented here with evidence can of course occur more frequently in communication between different nations. Therefore, special attention should be paid to language and especially context-specific language.

The level of scientific evidence that is achievable varies across different domains. For example, evidence derived from experiments is stronger than evidence derived from longitudinal tracking of data. However, it is not always possible to conduct rigorously controlled experiments (for example in relation to issues such as climate change or the long-term effects of smoking on cancer). This means scientists sometimes have to rely on the weight of evidence when drawing conclusions. This degree of uncertainty can in turn be exploited by those claiming there is no ‘good evidence’ for a phenomenon or that scientists have not yet ‘proved’ two phenomena are linked (Oreskes & Conway, 2010). As such, care needs to be taken in communications around ‘evidence’ and ‘proof’.

**Absence of evidence versus evidence of absence**

Another point of confusion in scientific communication relates to an absence of evidence versus evidence of absence; whilst the former refers to instances in which there is insufficient research from which to draw conclusions, the latter is where there is good evidence that two phenomenon are not linked. This distinction is not captured when scientists simply state that there is 'no evidence' for something; more precise language is needed.

## Can the public contribute to science and science communication?

Participatory research is where members of the public are involved in the research process, beyond that of a passive research subject (Eitzel et al., 2017; English et al., 2018; Kullenberg & Kasperowski, 2016). It can take a range of different forms, including community-engaged research, participatory action research and citizen science. In some instances, public involvement may be limited to data collection but in other cases it may include the development of research questions, data analysis, data interpretation and dissemination (English et al., 2018). Participatory research can have direct benefits for scientific communication when members of the public help decide on the best ways of presenting and disseminating information since this can help ensure it is both understandable and culturally relevant (English et al., 2018). Participatory research may also increase the scientific literacy of those involved, though this may be more likely to occur if it is a specific aim of the research project (Bela et al., 2016;

Kappel & Holmen, 2019). Additionally, where members of the public are involved in shaping research questions, this may lead to research that better meets their needs (English et al., 2018). Nevertheless, due to an absence of research, we do not yet know whether participatory research can increase social acceptance of science or trust in scientific institutions (Kappel & Holmen, 2019).

## Fact-checking

### The role of fact-checking organisations

Fact-checking is where an organisation evaluates the accuracy of claims made by politicians or of other information in the news or on social media. It is typically carried out by journalists or non-profit organisations (Nieminen & Rapeli, 2019). Research shows that fact-checking messages can increase the accuracy of people's beliefs but these effects are quite weak, especially when used to correct misinformation. Nevertheless, by holding political entities to account, fact-checking may help keep false statements out of public discourse (Walter et al., 2020).This may be because fact-checking statements are unlikely to link to the person's beliefs or values, so do not elicit an emotional response (Oeldorf-Hirsch et al., 2020; Walter et al., 2019; see section on Narratives). Nevertheless, by holding political entities to account, fact-checking may help keep false statements out of public discourse (Walter et al., 2020).

**How can we promote fact-checking  among the general population?**

In a world in which misinformation, fake news and conspiracy theories are spreading like wildfires, it is crucial to train the general public in thinking critically. Checking your sources of information before sharing them with others is essential. This is where we should consider the concept of boosting. Boosting is a policy approach that targets people's competences and thereby helps people make good, informed decisions by and for themselves (Hertwig & Grüne-Yanoff, 2017). A boost is an intervention that enlists human cognition, the environment, or both to foster people's existing competences or develop new ones (Hertwig & Grüne-Yanoff, 2017, Herzog & Hertwig, 2019). The objective of boosts is to foster people's competence to make their own choices—that is, to exercise their own agency (Hertwig & Grüne-Yanoff, 2017). Boosting is therefore a key concept for science as collective intelligence, giving people the right to practice their own agency and letting them make the best decisions for themselves. "Pledge to pause" is an already existing initiative that can be classified as such a boost. "Pledge to pause" tries to tackle the problem of  people sharing information online rapidly, without ever thinking twice about it or in many cases even having looked at the source prior to sharing it. The initiative encourages people to take a pause before forwarding a message, retweeting a story or sharing a video they saw in their feed by first asking yourself the following five questions: 1. WHO made it?, 2. WHAT is the source?, 3. WHERE did it come from?, 4. WHY are you sharing this?, 5. WHEN was it published? (Verified |

#Pledgetopause). You can actively take part in the initiative by posting a GIF or image (provided on the website) to your social media channels with a short informational text.

Another strategy that allows people to quickly and effectively verify online information and a source's trustworthiness is lateral reading. Lateral reading can also be classified as a boost as it targets specific competences. When assessing a website's credibility, most people tend to read vertically. They stay on the site and assess different features like the name of the organization, whether the site has an official looking logo etc. (Breakstone et al., 2021). A strategy used by professional fact-checkers is that of lateral reading (Brodsky et al., 2021, Wineburg & McGrew, 2017). Instead of staying on the site, they turn to the broader web and open new tabs to get more information about the organization, people mentioned on the website etc. Lateral reading is a strategy that once learned produces more warranted conclusions about information online in just a fraction of the time needed by people who read vertically (Wineburg & McGrew, 2017). Lateral reading can be learned by everyone. Previous studies have shown great success. University students were taught the principles of lateral reading and improved significantly,  engaging in lateral reading more often post intervention (e.g., Breakstone et al., 2021; Brodsky et al., 2021). These findings inform efforts to scale this type of intervention in higher education but also in the general public. A Youtube video by the Stanford History Education group is a great start to learn more about it. Effective boosts like

these help us to communicate information more efficiently and counter the spread of dangerous misinformation.

## Transparency

### Conflicts of interest

Recent decades have seen an increasing public demand for transparency, in particular mandatory disclosures of conflicts of interest and potential bias from professional advisors (physicians, financial advisors etc.) and scientists conducting research (Sah, 2017; Demski, 2003). At first glance, the logic for disclosure is compelling. In principle, disclosure should allow recipients to adjust and potentially discount the information they receive for any potential bias. In reality, however, even if recipients paid attention to the disclosure, their decision on what to do with it is likely to be sub-optimal (Loewenstein et al., 2011; Sah et al., 2013; Sah et al., 2019; Sah & Feiler, 2019). In order to accurately discount any biasing influences, the recipient must possess an accurate mental model of how much the information has been biased. Without such a model, what does a recipient do? Ignore the information completely or discount just a little? A myriad of psychological factors has shown surprising and unintended consequences of disclosing bias or conflicts of interest (Sah, 2017; Loewenstein et al., 2011; Sah et al., 2013; Sah et al., 2019; Sah & Feiler, 2019; Sah, 2019; Fung et al., 2017), including increased trust in advice given when one discloses their 'bias' – an effect known as "*disclosure's expertise cue*" (Sah et al., 2016; Sah et al., 2018).

Despite these unintended consequences, recipients have an ethical (and often legal) right to receive such transparency (Tattersall et al., 2009; Miller & Wertheimer, 2009). Penalizing advisors for giving obviously biased advice or information with fines or sanctions may help improve the efficacy of disclosure (Church & Kuang, 2009) but unfortunately, bias is not only difficult for recipients to determine in real-world situations but it is also not an easy task for regulators to determine. For professional advisors, such as physicians, in many situations (e.g., deciding between medical treatments), multiple options exist, and it can be impossible to determine which advice is best and least biased (Sah, 2015). People have a right to receive accurate and complete information and if regulators can learn how to enhance disclosure's effectiveness, disclosure, in the sense of providing as close to perfect information as possible, is desirable. Transparency works well when personalized and users are provided with information they need when they need it.

**Values**

Nevertheless, these more formal transparency-related practices are unlikely to capture scientists' underlying values, which could also influence the conclusions they draw from their research as well as the type of research they engage in. Values refer to desirable end-states or behaviours and different people will place more or less emphasis on different values (Schwartz, 1992; Schwartz et al., 2012). For example, whilst one person may

prioritise safety and security another might give more weight to freedom of action. It is currently unclear how scientists could be more transparent about the values that underpin their research and any recommendations they make.

**Open science practices**

Adoption of open science practices can also increase perceived transparency. The open science practices represent a set of various, to some extent disciplinary-specific, research practices such as pre-registering hypotheses and analytical plans (i.e., preregistrations), making research data publicly available (i.e., open data), making research materials, notebooks, and protocols publicly available (i.e., open materials) and making analytical code publicly available (i.e. open code). Generally speaking, many advocated these research practices to increase the credibility of scientific evidence but also to work as "trust generating mechanisms" (Grand et al., 2012; Munafò et al., 2017; Nosek et al., 2015; Vazire, 2017). The idea behind this is that open science practices reinforce adherence to scientific norms such as those indicating integrity, competence and benevolence, which send strong signals of trust to the public (Jamieson et al., 2019).

Indeed, some evidence supports the notion that implementing open science practices enhances trust. Some limited evidence indicates that open science practices increase other researchers' trust in scientific findings (Field et al., 2020; Schneider et al., 2021; Song et al., 2021). For instance, scientists

perceived the studies adhering to open science practices to be more credible and trustworthy than those not adhering to these research practices. Furthermore, open science practices matter for the public's perception of scientific findings. In a recent nationally-representative survey, around 68% of the respondents said that open data and materials matter in their decision whether to believe in a scientific result or not, increasing trust (Funk et al., 2019). Some experimental evidence supports these claims (Song et al., 2021). On the other hand, the public trust-repairing strategies presented in a context of low replicability of psychology, including increased transparency, did not repair trust (Anvari & Lakens, 2019; Wingen et al., 2020). In these latter studies, however, participants judged scientific discipline as a whole rather than scientific evidence, which can account for the mixed findings. Thus, overall, some limited evidence supports the idea that communicating whether the scientific evidence followed open science practices can enhance the trust of the public and other stakeholders.

**Preprints**

Preprints provide scientists and researchers with more autonomy and transparency (Yesilada et al., 2021). Traditionally, research findings are disseminated through journal articles. A researcher submits their findings in a manuscript, which is then reviewed by a group of experts in the field. This process is called “peer review”. The manuscript usually takes some time to undergo this review process. In psychology, for example, this process is

estimated to take around 20 weeks (Huisman & Smits, 2017). Only after it has been accepted and reviewed, is it then published.

Preprints, on the other hand, are publicly available scientific papers that are submitted to a public server ahead of the publication process (Mudrak, 2020). These servers allow the scientific community, as well as any member of the public, to have early and free access to said research. Publishing your research as a preprint makes the content more accessible and transparent to a greater range of people, potentially lowering barriers to participation (e.g. Yesilada et al., 2021; Sarabipour et al., 2019). This is an important consideration, not only when thinking of science as collective intelligence but also given that the academic publishing system underrepresents women and minority groups (Clark & Horton, 2019; Mertkan et al., 2016). Taking a look at the role of preprints during the COVID-19 pandemic, the science of intelligence aspect becomes even clearer: The scientific community responded rapidly, releasing over 125,000 COVID-19- related scientific articles within only ten months after the first confirmed case, 30,000 of which were hosted by preprint servers (Fraser et al., 2021). During a crisis the collective rapid production and dissemination of knowledge is a critical factor (Lipworth, Gentgall, Kerridge, & Stewart, 2020). The accessibility to research that preprints offer goes beyond rapid dissemination. Preprints show how science of collective intelligence is already being executed. Preprints can offer a transparent way of offering research findings to the public online and may be a great way of practicing science as collective

intelligence already.

PURPLE GROUP SECTION:

As we have seen in earlier sections, science communication can benefit greatly from harnessing collective intelligence to collect, evaluate, and disseminate scientific evidence. However, the process of doing so is not without its challenges. In this section, we review two challenges involved in communicating as a collective, namely how to form a collective that captures sufficient epistemic diversity and how to then present this communication from the collective in an effective way. Given that the landscape of communication today is highly influenced by technological advances, we also discuss in the context how technology influences the formation of collectives and the communication process, and the challenges and opportunities this creates for collective communication. Throughout the section, we suggest how these challenges could be overcome and highlight questions that we need to resolve through future research that would better equip us as behavioural scientists to meet the challenges discussed.

**Composition of the collective: Who gets to participate?**

Especially at times of crisis, a plethora of messages from individual experts communicating different perspectives and pieces of information can lead to

confusion. For scientific governmental institutions, managing the “infodemic” has taken the approach of “speaking with one voice”, providing policy advice for decision makers and pointing the public to the right sources with credible information. One of the extreme examples here is the COVID-19 crisis, where far-reaching public health measures that directly affect people’s everyday life are taken by politicians, informed by evidence-based policy advice by public health institutions and other stakeholders. Here, the work of individual experts converges in task forces and think tanks.

However, how does a collective ensure openness for new and potentially contradicting information, and how does it avoid biases and groupthink (Schippers & Rus, 2021)? How does one navigate this process of providing policy advice, acknowledging both individual expertise and scientific independence while ensuring collective evidence-based communications at institutional level? Drawing on collective intelligence could enhance the visibility of consensus for scientific positions, but some key challenges arise stemming from *who* forms that collective. To support the accurate synthesis of available evidence, a scientific collective needs to be epistemically diverse and guard against biases. Our understanding of what constitutes disinformation and what determines credibility is an example of collective knowledge construction: a variety of stakeholders are involved, both formally and informally, in the process of constructing our conceptualization of these key concepts. Media and fact-checking organizations, scholars,

governmental bodies, NGO's, tech companies, politicians, and publishers are just a few of the stakeholders who shape our current understanding of what constitutes disinformation and what determines credibility.

The involvement of multiple stakeholders particularly critical because often, there is no universal truth that can ground the definition of what is credible information (Molina et al., 2019; Southwell et al., 2017). For example, the multitude of different definitions available represent numerous perspectives on the issue of credibility. Some definitions of disinformation (and related concepts such as misinformation and "fake news") emphasize attributes of the content itself (Sharma et al. 2018) or the process of creating it (Lazer et al., 2018), while others focus on the intent (e.g., deliberate or not) (Lazer et al., 2018; Tandoc, Lim, & Ling, 2018) or motives (e.g., political, financial, etc) of the creator of the information (National Endowment for Democracy, 2017), the expertise of the source (Vraga & Bode, 2020), or the impact on the recipient (Kuklinski, Quirk, Jerit, Schwieder, & Rich, 2000; Nyhan & Reifler, 2010; Vraga & Bode, 2020). Additionally, some scholars also consider the way information is spread online (e.g., the influence of automated accounts and tactics like hijacking trends and practices in search engine optimization (SEO) (Vraga & Bode, 2020). Efforts have also been made to classify misinformation into different categories based on distinguishing characteristics across multiple dimensions, including message, source, structure, and network (Molina et al., 2019). Ultimately, individual

judgements and decisions around credibility include the evaluator's own cognitive biases, as well as cultural influences, politics, organizational policies and practices, and discipline-based norms and standards. As such, relying on a single individual—even one with domain expertise—limits our evidence base.

Relying on expert consensus can help delineate the boundaries between truth and falsehood, but delineating what constitutes expert consensus (as opposed to simply collective consensus) is in itself a challenge. Statistically, the number of experts in any domain will always be vastly outnumbered by the number of non-experts that exist, meaning that without a way to verify expertise, it becomes difficult to maintain scientific credibility. A collective scientific position can be manufactured, as was observed in the field of climate science, where the Global Warming Petition Project, funded by fossil fuel industry and lobby groups, collected public signatures for the statement that "humans aren't disrupting the climate"—notably, most of the signatories were not actually experts (Cook et al., 2018). The recent pandemic is also not short of examples of groupings and activities that on the face of it, appear to be collective initiatives to examine, evaluate, and communicate scientific findings. As an example, the Great Barrington Declaration, which supported the lifting of Covid restrictions in favour of "focused protection" of the vulnerable (ignoring the practical impossibilities of doing so, among other facts), cites over 900,000 signatures to date, of

which over 50,000 declare themselves to have medical or public health expertise. Without closer examination, one might assume that there is large scientific support—even consensus—for this position, even though numerous public health organisations, including the World Health Organization, have rejected the scientific basis of the proposal. Checking the declaration shows immediately that signatures are not vetted—meaning it is impossible to know if the self-declared experts are indeed such—and some signatories are even verifiably fake. Some form of gatekeeping is a necessity if science communication as a collective is to retain credibility.

However, the tension lies between the need to maintain credibility in expert consensus while fostering trust in scientific experts. Many of the same historical and ongoing phenomena that have contributed to inequalities in status, representation, inclusion, and knowledge production — namely, discrimination, prejudice, and injustice — have also resulted in distrust of institutions and expert knowledge in many communities, ultimately leading to disparities across a variety of health and disease outcomes (Best et al., 2021; Bogart, Wagner, Galvan, & Banks, 2010; Dale et al., 2016; Quinn et al., 2017). The effects of collective distrust, particularly among racial minorities, have been apparent during the COVID-19 pandemic and are believed to be a significant contributor to racial disparities in COVID-19 outcomes in the U.S. (Best et al., 2021). As explicated by Best and colleagues (2021), “Environments of institutional distrust drive individualized perceptions of risk

and decreased adherence to public health recommendations and interventions. Institutional distrust is more prevalent among racial/ethnic minority and low-socioeconomic status populations, especially African Americans; distrust is shaped by individual and collective experiences of injustice; ultimately, it is injustice that exacerbates health inequities." Experiences of injustice leading to distrust may also make members of minority groups more susceptible to misinformation (Roozenbeek et al., 2020), as institutional and expert sources may be perceived as less trustworthy, resulting in rejection of authoritative information and increased information-seeking through alternative channels (Pierre, 2020; Quinn et al., 2017) — a phenomenon termed "inequality-driven mistrust" (Jaiswan, LoSchiavo, & Perlman, 2020). Furthermore, the rejection of authoritative sources can open up an "epistemic vacuum" that drives individuals "down the rabbit hole" of conspiratorial sources and low-credibility content as they search for alternative sources and explanations (Pierre, 2020). From this perspective, conspiracy theories and misinformation are conceptualized as the product of contested epistemic authority (Harambam & Aupers, 2015).

The lack of diversity and representation in science, and how existing conceptions of expertise may perpetuate it is a legitimate concern, rooted in historical events that reverberate in the present through enduring social hierarchies, that the process of knowledge-production and the construction of what constitutes legitimate or credible information may perpetuate long-

standing inequalities and contribute to the marginalization of voices from groups such as women, non-whites, and citizens of developing nations (Almeida, 2015). Additionally, some scholars argue that the epistemologies of historically dominant social groups are so embedded in contemporary society that they have come to be seen as “natural” and “just the way things are”, which makes them easy to overlook and unconsciously reproduce if not challenged through a deliberate process of deconstructing scientific consensus-building, information gatekeeping, and sensemaking (Almeida, 2015; Thapar-Bjorkert & Farahani, 2019). One prominent example that demonstrates the potential challenges of relying only on expert consensus relates to the inclusion of traditional, local, and Indigenous knowledge sources. Often, the knowledge possessed by locals is vital but not captured by contemporary scientific methods. In some cases, this knowledge only exists in the minds of those who possess it (Sutherland, Gardner, Haider, & Dicks, 2013). Based on existing standards that prioritize processes such as peer-review and fact-checking in the conceptualization of credibility, this information would, in many cases, not be deemed credible. Yet the neglect of these sources of knowledge could undermine trust, particularly if expertise is perceived as a form of discrimination.

Navigating the tension between credibility and trust in collective communication may involve dedicated strategies to address diversity and representation in the processes of evidence synthesis, communication, and

decision-making. For example, engaging members of communities that have been most affected by COVID-19 is a matter of both ethical and practical importance. Genuine outreach and community engagement are necessary to build trust and start healing the deep wounds of injustice, and also to ensure that the formulation and communication of information are carried in culturally appropriate ways (Best et al., 2021). Elevating trusted sources within marginalized communities and leveraging trusted information-sharing processes such as intergenerational communication are two promising strategies to help build institutional trustworthiness (Best et al., 2021).

The pursuit of diverse participation can also be formally translated into practice through a process referred to as the institutionalization of consensus and diversity (Montana, 2017). In response to criticism about the lack of diversity in previous international scientific collaborations (for example, the Intergovernmental Panel on Climate Change (IPCC), which was criticized for having limited participation from developing countries and lacking representation from a diverse representation of academic disciplines; Hulme & Mahony, 2010), the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) produced a conceptual framework for decision-making that offers an "explicit, formal incorporation of knowledge systems other than western science" (Diaz et al., 2015). The decision-making framework was developed over a two-year period during which specialists from a variety of scientific disciplines and knowledge

systems worked through processes such as negotiation, shared ownership, and establishing situated practices to produce an integrated model of the interactions between nature and humans, with the goal of strengthening the "science-policy interface." Prior to being finalized, the IPBES framework was submitted to open comments from more than 100 governments and numerous NGO's. Rather than attempting to avoid or resolve conflict and disagreement, the IPBES framework embraces divergent perspectives and assessments in the decision-making process. For example, when defining the framework's core elements, a decision was made to allow different knowledge systems to define them according to their own categories. As described by Diaz and colleagues (2015):

> *IPBES has three distinctive features. First, it must engage, in the process of defining questions, assessing trends, and identifying solutions, a great diversity of stakeholders including policy makers, practitioners, civil society organisations, and the private sector. Second, it aims to incorporate knowledge from a variety of sources, including not only the natural, social, and engineering sciences but also indigenous and local knowledge (ILK). The inclusion of ILK is not only a matter of equity but also a source of knowledge that we can no longer afford to ignore. Third, IPBES goes beyond producing assessments to include capacity-building, development of policy tools, and catalysing the generation of critical new knowledge.*

Although such a framework does not guarantee that diversity of participation and representation are achieved, it does make it more far likely that we would recognize it if it is missing. It also facilitates transparency in decision-making, which could be further emphasized by formalizing transparency principles and procedures. Given the critical importance of gaining and maintaining public trust, any lapse or gap in transparency would risk undermining even the best science.

One of the predominant concerns surrounding transparency—or the lack thereof—is the often invisible and silent role of power in the production and dissemination of knowledge. By choosing to emphasize certain truths, perspectives, and methodologies, we are also choosing to leave others out. Although these decisions should be, and typically are, guided by the strength of the evidence and the relevance and implications of the findings, those seemingly objective evaluations may still be influenced by subtle biases and cultural variations, as well as embedded value systems and norms, including those espoused by western science. As such, establishing formal procedures to encourage, facilitate, and enforce transparency is particularly important in areas such as evaluating the state of science and specifying the criteria used to evaluate information and sources. Additionally, there is a critical need for transparency surrounding the expertise of those involved in decision-making and why they were chosen to be decision-makers.

**The reception of collective science communication: How do people respond?**

It is not always easy to determine who is the audience of science communication. Depending on the context, scientists may be communicating to policy-makers, with the objective of helping them understand and incorporate often-complex information into policy-making. They may also be communicating to the public at large, to provide evidence-based scientific advice or guidelines on a critical issue, as in the case of the climate crisis and the COVID-19 pandemic. In either case, the onus is partially on experts—including those operating as a collective—to communicate information in an appropriate way such that their audience can correctly identify, incorporate, and interpret the advice. The importance of this is magnified when science informs democratic policies, particularly in a crisis where decisions are frequently as important as they are difficult, with potentially drastic consequences for many people.

Communicating as a collective presents an advantage in itself, in that it can showcase the level of expert consensus and thus highlight the strength of the evidence for a given position. Consensus is important because it can form the basis for people's decision-making, especially when the issue at hand is complicated (Budescu & Chen, 2014; Surowiecki, 2005). Groups seeking to misrepresent, distort, and cherry pick scientific evidence

masquerade as collective initiatives not because there is consensus for their position, but because they understand the power of collective science communication and seek to weaponise it (Tomori, 2021). Indeed, when disinformation lobby groups wished to distort the science on climate change, they chose to undermine the level of actual, widespread consensus among scientific experts on the human causes of global warming by creating an illusion of expert disagreement through their Global Warming Petition Project (Cook et al., 2018). The damaging impact of this attack on consensus is still felt today as the myth that scientists disagree about the causes of climate change continues to circulate (Readfearn, 2016) and hinder acceptance of climate change (van der Linden et al., 2017). Notably, there remains a "consensus gap" in climate change, where on average, the public thinks only 67% of climate scientists agree that global warming is man-made (the actual consensus is 97%; Leiserowitz et al., 2017). Strikingly, this distorted public perception also affects science teachers, which impacts the way climate science is taught in schools (Plutzer et al., 2016).

We should not underestimate the ability of disinformation lobby groups to undermine systems created for collective science communication such that collectively-backed evidence gets weighted equally against collectively-backed opinions. Flagging these motives and vested interests by highlighting who is funding disinformation could be one way to combat it. However, it is insufficient to focus on uncovering hidden affiliations. For one, disinformation lobby groups often go to great lengths to conceal their funders (e.g., Rotman

et al., 2022)—by the time an investigation turns up sufficient proof, damage will already be done. For another, all scientists have beliefs, values, and worldviews that may differ from others, and most have a funding source, whether it is a National Research Council, Non-Governmental Organisation, or an International Research Grant. Transparency over the funding source and disclosures about the role and purpose of funding sources should certainly be required for all scientists. But there is no point for science communication to engage in a debate about which funding sources should be considered legitimate. Indeed, such a debate leaves scientists open to common conspiracist rhetoric that “mainstream” experts are also being paid and therefore corrupt.

Rather, collective science communication needs to pick out disinformation efforts on the battleground of evidence. There are certain distinguishing features of disinformation and anti-science rhetoric, such as the use of fake experts to inflate support or cherry picking evidence to reach a desired conclusion. We need to direct efforts towards communication systems that can showcase these flaws. Promising examples include the ALL-IN approach (ter Schure & Grunwald, 2021), which co-ordinates and collates emerging evidence in real time, submitted by experts independently pursuing the same research question. As more of such initiatives are generated, an open question for scientists wishing to communicate as a collective will be to assess the extent to which they can guard against information distortion or evidence bias.

Second, we may need to unpick what consensus is being sought *on*. We may disagree with the primary conclusion of the Great Barrington Declaration that restrictions on the non-vulnerable should be lifted in favour of restricting the vulnerable, but disagreeing here does not mean disagreeing with all of the premises. As an example, an open letter to the UK government during the early stages of the COVID-19 pandemic (Hahn et al., 2020) was a collective endeavour expressing disagreement with a specific underlying proposition that there was evidence for the concept of "behavioural fatigue".

Third, when we seek out evidence, we need to challenge our own cognitive biases as scientists—including the tendency for confirmation bias (Nelson, 2014; Masnick & Zimmerman, 2009; Nickerson, 1998). In the search for consensus for a scientific (or indeed, anti-science) position, there is a tendency to ask, "who and what evidence supports this conclusion?" In fact, we need to be asking, "what are the conclusions supported by the evidence?" A collectively intelligent science communication system needs to give the opportunity for evidence-backed dissent.

Fourth, while we could posit that more accurate public perception of consensus should encourage better decision-making, we in fact need more evidence to guide our understanding of how different levels of consensus are perceived and incorporated in the decision-making process, particularly given that behavioural science has already shown that decision-makers often (a) ignore (Golman & Loewenstein, 2018; Loewenstein et al., 2014; Golman

et al., 2017), misinterpret and bias (as a result of cognitive biases; Tversky & Kahneman, 1974), or (c) re-shape information to fit beliefs or identities (Nickerson, 1998; Kahan, 2017). One might expect such "errors" to be more frequent during unimportant decisions, when decision makers are inexperienced, or when decisions rely on value judgments rather than objective evidence. However, policy makers might be as likely as other decision makers, including experts (Fitzsimons & Lehmann, 2004), to ignore information willingly, or to interpret it in a biased way. The question of whether policy makers are susceptible to information ignorance, cognitive biases, or motivated cognition is interesting in and of itself. With regards to the role of collective intelligence in science communication—particularly to policy-makers—these biases in decision-making have implications for whether a collective of scientific experts, compared to individual experts, can better help their audience incorporate information in an unbiased way.

One of the posited benefits of collective science communication is that collectives may be perceived as less prone to biases—a factor that is generally important to policy-makers and should make communication with them easier. However, policy-makers' own biases in information processing—such as whether they would be more likely to ignore information or experience other cognitive biases—could interact with whether information comes from an individual or a collective. A collective of experts would thus benefit from knowing what to expect about policy-makers' biases when designing their communication strategy. For instance, advice can cause

psychological reactance when unsolicited (Fitzsimons & Lehmann, 2004) or be less effective when coming from a self-interested adviser (Kuang et al., 2007). Information coming from a perceived out-group may also trigger identity-protective cognition that leads decision-makers to reject the information.

To avoid these pitfalls, an expert collective might need to maintain two-way channels of communication and recognise when advice is solicited. A collective may need to think about appropriate management and disclosures of self-interest for members and whether it needs to pay more attention to these issues than an individual expert in order to communicate effectively. The collective may consider strategies to mitigate being perceived as an out-group—highlighting the need for diversity in collectives and the chance for disagreement (Moore & MacKenzie, 2020). The answers to these questions are currently unclear and deserve further investigation.

A further unanswered question involves the perception of collective communication when it reflects different levels of consensus (or dissensus). Policy makers might have a preference for information that, if coming from a collective of experts, represents a consensus (Golman et al., 2016). In fact, perceived consensus can reduce ideological biases on climate change (Goldberg et al., 2020). However, we do not know whether consensus information could also reduce the impact of other cognitive biases on decision-making. For example, when information is the result of dissensus, a

challenge for expert collectives could be that policy-makers might prefer in this case to receive information from individual experts (thereby avoiding having to resolve the inherent uncertainties around dissenting advice). A further challenge could occur when an expert identifies with one of the groups in a dissenting group of experts, since this might induce the expert to bias, discount or ignore important information coming from the "out-group".

These are important challenges that scientists should investigate further and to tackle when communicating information to policy makers as a collective. An effective collective expert communication strategy would ideally be built on the relevant scientific evidence. Taking such evidence into account will likely improve the effectiveness of a collective communication strategy and increase its impact on policy decisions.

**Forming and communicating as scientific collectives in the age of technology.**

Science communication today takes place increasing over the Internet. Journals publish scientific articles online, scientists share data and code in online repositories, and academic ideas are increasingly debated on public online channels such as Twitter. The migration of academic publication, data, and discourse to online spaces is highly beneficial for transparency and openness in scientific research. However, online spaces also open science up to abuse and manipulation, especially as artificial intelligence such as machine learning-based tools, chatbots, algorithmic targeting, deepfake

technology, and social engineering become more common as tools to influence individuals and collective thinking (Busuioc, 2020).

An underlying threat posed by much of this technology in the online ecosystem lies in its potential to deceive. Deception represents an intentional act performed by manipulating information in some manner with an instrumental goal of creating or maintaining a belief that the communicator considers false (DePaolo and De Paolo 1989; Xiao & Benbasat, 2011). There are different ways in which we can encounter deception in the scientific communication ecosystem, through concealment, omission, or falsification, including by manipulating the information content, presentation, and generation (Buller et al., 1994; Burgoon et al., 1994). Deception can also arise from the portrayal of information as true that is later retracted as false, notably when produced and shared rapidly ahead of the slower peer review process, before collective intelligence can intervene, and when scientific expert consensus is slow to form (Baum, 2018; Cook, Ecker, & Lewandowsky, 2015). Although the intent in such cases may not always be to deceive (but equally, there are cases where it is deliberate), there remains a detrimental impact on scientific knowledge (Bar-Ilan & Halevi, 2017; Greitemeyer, 2014).

The difficulty with deception in the context of science communication is that individuals have issues detecting deception. This may partly be due to a lack of technical knowledge about the subject matter (although individual experts themselves are not always immune to deception within their domain;

Lindsay et al., 2018; Lagerspetz, 2020), as well as a lack of communication cues that are usually present in interpersonal communication. However, deception is further perpetuated through AI tools that blur the line between truth and fiction. For example, deepfake technology can manipulated videos such that one could be portrayed as saying anything “on camera”. Communication bots allow misinformation to be disseminated rapidly, making it even harder for debunking efforts to keep up. More insidiously, the algorithmic profiling of individuals through malicious communication campaigns has sought to magnify individual and collective biases, helped along by existing algorithms that prioritise content that support existing biases, generate negative feedback loops, and create echo chambers—all of which make it harder to identify and correct deceptive content and misinformation.

Due to the difficulty that any one individual—expert or otherwise—would face in detecting deception in any communication, especially online, there is a role for collective intelligence to step up. However, just as AI has accelerated the ability to deceive, the scientific collective needs to harness AI-based tools to enhance its efforts in communicating real evidence by identifying, predicting, and preventing manipulation and misinformation in scientific communications. Here, AI can be leveraged instead to evaluate the level of information manipulation, assess the potential human bias, detect patterns, sort populations of interest, and make predictions (DeVoss, 2017; Henman, 2020; Miller, 2018; Silberg & Manyika, 2019; Tomori, 2021; Valera,

Singla, & Gomez-Rodriguez, 2018). For example, AI's ability to spot patterns can be used as a detection tool, allowing more rapid detection of plagiarism, communication trends, and deceptive language use. It can also be used to extract insights from large datasets, identify signs of data manipulation and erroneous statistical analyses. The same AI used in network identification could be valuable in identifying topic experts and potential reviewers of scientific work, recognising who and what influences communications, detecting connections to misinformation campaigns and groups.

A good way to integrate AI into science communication would be to adopt an ecosystems framework where scientific knowledge can be co-created, co-curated, integrated, and aggregated in a collective manner, while considering the key spheres of the scientific environment: micro, meso, and macro (Osborne, 2021; Osborne et al., 2021; Petrescu, 2019). Scientific communication based on collective intelligence has a high potential for such co-creation (and co-destruction) of value for all its stakeholders (Bonabeau, 2009; Malone et al., 2010; Wise, Paton, and Gegenhuber, 2012), and its effectiveness depends on the ability to involve all stakeholders in value co-creation and the prevention of co-destruction, based on the profiles of participants and their motivations (Osborne, 2021; Osborne et al., 2021; Petrescu, 2019).

Scientific communication based on collective intelligence and promoted with the use of AI-based technologies can incorporate stakeholders from each of the three levels of the ecosystem. At the micro level, this includes individual researchers and citizens. At the meso level, this includes R&D groups, universities, and corporations. At the macro level, this includes interest groups, government and society. Within this framework, scientists can apply AI-based tools in the relevant contexts where it is currently distorting evidence and deceiving individuals. For example, at the macro level, machine learning software can be used to neutralise algorithm bias and echo chambers, while automated text analysis, natural language processing, and social network analysis can help to uncover disinformation groups and manipulation trends. At the meso level, AI tools can provide collaboration interfaces and platforms to facilitate collective organisation and social network analysis can help identify and connect positive influencers, scholars, celebrities, and journalists to deliver collective communication efforts. At the micro level, deception detection software can be employed in counteracting AI-based manipulations such as deepfake technology, while information inoculation and strategic, refutational correction of misinformation could be deployed to pre-emptively educate individuals against disinformation (Banas & Rains, 2010; Baum, 2018; Cook, Ecker, & Lewandowsky, 2017), particular algorithmically-targeted disinformation.

Applying this framework within the field of infodemiology could also help in cases where rapid and collective crisis knowledge management is required–

for example, during the COVID-19 pandemic, infodemic management has been identified as a critical area of practice by public health organizations including the World Health Organization (WHO; Briand et al., 2021; Mavragani, 2020; Eysenbach, 2009). In an infodemic management infrastructure, both individual experts and the collective can each play their own role in contributing to the decision-making process and collective narrative through risk communication and community engagement. Infodemic managers can enable science communicators to work as a collective, working through a system to ensure that people have the right information at the right time in the right format (WHO, 2021). In practice (Eysenbach, 2020; Tangcharoensathien et al., 2020), it starts by listening to population needs, through social listening (or: 'infoveillance') to help establish a more proactive approach to communication. In addition, improving science and media literacy help to build resilience, along with peer-review and fact-checking, which encourages quality improvement and knowledge refinement. Sharing accurate and timely information helps to translate knowledge, in the context of other influences for e.g. commerce or politics. Infodemic management cannot prevent outbreaks of misinformation, but can help shape the narrative and mitigate the spread of mis- and disinformation. Ultimately, it strengthens systems and helps to (re)build trust in science and institutions.

In infodemic management, social listening is an essential tool that could be enhanced with advances in technology. Social listening can take place both

on- and offline, and monitors with the ability to identify information voids, as well as the early detection of outbreaks of misinformation (Purnat et al., 2021). While it is common practice for businesses to monitor social media channels for mentions of their brand, competitors or product, to monitor its reputation (Newberry, 2021), it is still just starting to find its way in the public sector. The increase in online communications has, in combination with computational powers and AI, enabled real-time social listening, such as the EARS platform that tracks online COVID-19 conversations (Purnat et al., 2021b). Tracking the narrative can help science communicators to understand what people are looking for, because social and conventional media sometimes get ahead of the evidence. When these information needs are addressed by targeted messaging, promoting and supporting resilience contribute to behavioural change -- such as lifestyle adaptations in favour of protecting the climate, health behaviour (e.g. nutrition, vaccination), as well as voting in elections – and community engagement.

The potential to use AI against deception (rather than to promote it) and enable greater visibility of evidence (rather than obscure it) presents many opportunities for collective intelligence in science communication. However, questions remain about how best to do so. Here we highlight four main issues that a research agenda on the intersection of AI and collective science communication should address.

First, how much can, and should, digital communications algorithms be controlled in the interest of accurate scientific communication—and critically, who should do so?

Second, how can the concept of open data and open code be integrated in scientific and societal collective communication?

Third, which actors within the scientific ecosystem should be involved in the monitoring and mediation of collective scientific communication with the general public?

Finally, how can the concept of scientific consensus be reflected in communication algorithms in the scientific ecosystem?

Addressing these questions would form an important first step towards harnessing AI in service of collective science communication rather than simply a challenge to be overcome.

YELLOW GROUP SECTION:

Proof of Scientific Method

*Consensus-as-proof and explaining how scientific knowledge production works*

**Evidence synthesis**

Progress in scientific knowledge production is mostly based on findings of single or sets of studies about scientific, policy or management questions. These are often communicated to public audiences. Describing how study findings relate to the overall available body of scientific evidence increases transparency and allows evaluating the progress made in a field. Evidence synthesis demonstrates how variable study findings are and the degree to which findings align with relevant theory. Evidence synthesis has fed into a wide range of globally pressing challenges including climate change, biodiversity loss, or the COVID19 pandemic (Elliot et al. 2021) for making evidence-based policy decisions. At the same time, evidence synthesis needs to integrate and communicate uncertainties in and across scientific studies.

There are established methods for evidence synthesis that vary according to the practices of different research fields.  Meta-analyses statistically analyze effects from single studies. They can include studies about the effectiveness of an intervention in a population of interest compared to a control condition (Cheung & Vijayakumar, 2016), or they can assess effects of relevant moderator variables (see Abrahamse & Steg, 2013 for an example). Other methods catalog and describe evidence more broadly. For example, systematic reviews can include studies that employ different measures and thus can not be statistically combined. Systematic maps can collate articles with and without empirical data (James, Randall & Haddaway, 2016). A narrative review may discuss literature about a broader question of both practical and/ or theoretical relevance (Dixon-Woods,

Young, Agarwal, & Sutton, 2005). Those methods can be complemented by other methods for assessing the amount and quality of evidence and scientific agreement. Examples of this are expert surveys for assessing scientists' views about a specific question, such as whether climate change is human-caused (Cook et al. 2016) or the degree of future sea level rise (Horton et al. 2020). Peer-reviewed reports collate evidence for policy making, involving a large number of experts. Examples are reports of the Intergovernmental Panel on Climate Change, or the Intergovernmental Panel on Biodiversity and Ecosystem Services.

Within and across disciplines, guidelines set transparent standards for increasing quality and replicability of evidence synthesis (Haddaway & Macura, 2018; McKinnon, Cheng, Garside, Masuda & Miller, 2015). Guidelines ask authors to precisely describe the terms used, and how terms were combined when searching for studies in scientific literature databases. They also ask authors to describe when and where they searched existing scientific literature, whether and what type of "grey" literature was included, and to provide inclusion and exclusion criteria for studies identified during the search process (Berrang-Ford, Pearce & Ford, 2015). Examples are Reporting Standards for Systematic Evidence Synthesis (ROSES) in environmental sciences, the Preferred Reporting Items for Systematic reviews and Meta-Analysis (PRISMA) in health, or the Campbell Collaboration in social policy making.

Recent methods for evidence synthesis address earlier issues of feasibility and reliability. Large-scale evidence synthesis methods like meta analyses and systematic reviews are characteristically labor- and time-intensive (Sutherland & Wordley 2018), and therefore costly. Additionally, systematic reviews turn quickly out of date as they exclude most recent studies when responding to uncertain and high risk events, such as the COVID19 pandemic. After having established the criteria for subsequent studies to be included, researchers regularly monitor new publications and update their synthesis, often using machine learning approaches (Elliot et al., 2021). Examples include Living Evidence by the Australian government, an online site where evidence about COVID19 is regularly updated (Elliot et al., 2021); "living systematic reviews" by the Cochrane Collaboration ; and Conservation Evidence who collate evidence about ecosystem conservation and provide tools for decision-making and for increasing decision-making transparency (Christie et al., 2021). These and similar methods also allow for agility in adjusting policy guidelines to align with latest scientific findings (Elliot et al., 2021).

Evidence should also be qualified, so that evidence synthesis describes both the sources and types of uncertainty in order to allow for better understanding and for boosting trust in how scientific evidence is interpreted in the policy-making process.

I. Coverage Uncertainty - we *don't* know what we don't know

Evidence synthesis does assess how well a phenomenon relevant for policy decisions is scientifically understood. There may be hidden factors, uncertain causal effects, feedback loops or complex interactions influencing the phenomenon, all which may not have yet been researched. For example, in climate research, the role of clouds for the climate system is not yet sufficiently understood (REF).

For allowing audiences to better understand the implications of the epistemic condition “we don’t know what we don’t know”, we recommend to provide them with information about:

1. the research needed for better understanding the phenomenon
2. information about who communicates and what may be the underlying agenda of the communicator when describing uncertainties (Tomori, 2021)
3. how we can practically cope with uncertainty about unknowns. This includes that uncertainty require being more rather than less concerned about an event, because the overall range of possible consequences is larger (Lewandowsky et al., 2014)

II. Observation Uncertainty - we *know* what we don’t know

Evidence synthesis describes the type of scientific data available about a phenomenon, including the samples studied and the methods applied for collecting that data, which in turn helps in identifying research gaps.

Knowing the type of missing data would in principle allow for better understanding the phenomenon and for knowing whether given results have been replicated. Evidence synthesis also supports drawing conclusions about the nature of available data from studies and observed effects, and can help to establish variability, bias, imprecision, and conflicting findings. Evidence synthesis may be complemented by estimating the degree of consensus among scientists (Kerr & van der Linden, 2021).

For allowing audiences to better understand what we know about what we don't know, we recommend to communicate:

1. the gaps that have been identified in evidence synthesis that need to be researched for better understanding the relevant phenomenon

2. how variable, imprecise, and biased the available data is, and what the scientific consensus is, assessed in, for example, expert surveys (Cook et al., 2013)

III. "Theoretical Fit Uncertainty" - how well do findings fit existing theory or models?

Evidence synthesis ideally includes evaluations of how evidence relates to existing models or theories about a phenomenon. This includes two aspects: how well a theory or model *fits* the summarized evidence and how well a theory or model *predicts* the phenomenon of interest. A model may be

biased, overly complex, or miss out on important factors, and thus, fail to predict synthesized findings.

For allowing audiences to better understand the relation between findings described by evidence synthesis and existing theories or models about a phenomenon, we suggest to communicate:

1. how much research summarized in evidence synthesis aligns with well-established models or theories
2. the gaps that may occur between synthesized evidence and well-established models or theories

In conclusion, there is already a framework for qualifying evidence in the evidence synthesis process, but there is also opportunity for further research on how target audiences perceive and understand the sources of uncertainty (with some exceptions, including Kerr & van der Linden, 2021 about perceptions of scientific consensus), for better understanding the science *communication* process.

**Consensus or Groupthink**

A scientific consensus is usually defined as a collective judgment or agreement of a scientific community on a specific proposition. For example, 97% of climate scientists agree that humans are causing recent global warming (Cook et al., 2016). Scientific communities also collectively agree on the link between tobacco consumption and cancer, or the absence of a

link between autism and vaccination. These consensuses are relevant for the scientific community because they can provide an indicator of the level of uncertainty of a scientific proposition. Moreover, communicating a scientific consensus can bring several positive benefits for the public, such as increased agreement with scientific results (Lewandowsky et al., 2012) and increased support for action (eg. vaccination; van der Linden et al., 2015). But how is a consensus identified? This is subject to scientific debate and research (Shwed & Bearman, 2010). In fact, there is not only one but several methods to identify a scientific consensus on a subject matter.

One method of identifying a scientific consensus relies on systematically reviewing research articles that deal with the matter at hand. For example, Oreskes (2004) searched the ISI database with the keywords "climate change" and reviewed 928 abstracts, published in refereed scientific journals between 1993 and 2003. She then categorized the abstracts using a self-developed schema and concluded that 75% of articles implicitly or explicitly agree that greenhouse gas emissions are responsible for global warming. The schema was used to divide research articles into six categories: explicit endorsement of the consensus position, evaluation of impacts of climate change (implicit agreement), mitigation proposals (implicit agreement), methods, paleoclimate analysis, and rejection of the consensus position. Research articles assigned to the first three categories were flagged as agreeing with the claim that greenhouse gas emissions are responsible for global warming. Articles in the other categories were either

not appropriate to derive a position or rejected the consensus explicitly. Other researchers use a survey-based approach that directly asks experts to provide their judgment about a specific proposition. The percentage of agreement in the survey is then used as an indicator of the scientific consensus. For example, van der Linden et al. (2015) used a survey result that 90 % of medical scientists agree that vaccines are safe as a measure of scientific consensus in their study. A third approach aims to provide a more unified method for analyzing consensus across domains by observing patterns of citation networks using network analyses (for more details see Shwed & Bearman, 2010). For example, Shwed & Bearman describe their approach as follows:

> *"In a network of asphalt roads, for example, communities are villages, cities, and states. In a network of scientific papers linked by citations, communities are groups of papers that deal with the same issues and cite each other. Papers that agree are likely to cite each other much more than their protagonists (Hanney et al. 2005), giving rise to communities of agreement. The simple intuition underlying our strategy is that when different communities are salient to the global structure, the field is contentious."*

Thus, the authors use a decline in citation network's community salience as an indicator of consensus formation. It is always advisable, to review results of several approaches if they are available. For example, Cook et al. (2016) conducted a review of measures of scientific consensus and reported that the results differ, but only within a narrow range at the top of the scale (i.e., 90% – 100%).

Separate from the method used for identifying a scientific consensus, the consensus that was reached might be wrong altogether. Whether researchers choose to ask experts, conduct a systematic review, or use network analyses to quantify a consensus, the result will always rely on judgements based on the body of evidence given at a specific point in time. Naturally, this evidence can change. In fact, it is a crucial element of science progress to be open to new data – even, and especially if, the new data challenges what was considered to be a fact. Whether new data poses a substantial challenge to an assumption previously judged to be true usually depends on the quantity and quality of the new and old data. Heuristics such as evidence hierarchies for evaluating study methods can be used to assess the relevance of data (Murad et al., 2016). These hierarchies usually start with single opinions as the lowest level of evidence and end with aggregates of randomized controlled trials - that is, meta-analyses as the highest level of evidence. Thus, a large-scale new meta-analysis that consists of several studies may prompt a re-evaluation of a previous consensus, whereas single opinions in comments or perspective articles may carry little weight in belief

updating. Studies can also be compared even when they are based on the same evidence level. For example, the GRADE approach (Grading of Recommendations Assessment, Development and Evaluation; Atkins et al., 2004) helps researchers to assess the degree of confidence in a new scientific finding by rating the amount of potential bias in the methods of a new study (e.g. restriction of results to specific populations). That is, the pressure to change a proposition becomes greater as the quality of a new contradictory study gets better and as more high-quality studies support the new finding.

This intrinsic feature of changeability separates consensus from dogma. A dogma is typically 'laid down by an authority as incontrovertibly true.' (Lexico, 2022). In line with this definition, a dogma immunizes itself against any attempt to reject its truthfulness while a scientific consensus is open to change if the change is based on scientific evidence that outweighs the consensus. Thus, scientific consensus is not dogmatic.

In an ideal scenario, a scientific consensus is a rule-based, unbiased indicator of epistemic validity of the existing scientific knowledge in a specific research domain. However, that is an impossible expectation because scientists are humans and thus, scientific endeavor overall and the process of consensus formation are also prone to biases – biases such as groupthink. Groupthink describes a dysfunctional process of how groups may conduct decision making under specific suboptimal conditions. Groups are by no means generally bad decision makers, but if a group is very cohesive and

that group faces specific structural faults (i.e., insulation of the group, lack of impartial leadership, lack of norms for methodological procedures, homogeneity of groups) and a provocative context (i.e., high stress from external threats, low self-esteem) then teaming up can become a barrier to an evidence based decision making (Janis, 1972; Turner & Pratkanis, 1998). The symptoms of dysfunctional groupthink are overestimation of the group, closed mindedness, and uniformity pressure. This kind of thinking perpetuates in-group members considering themselves to be morally superior to any out-group member, stereotypes about outgroups, searching for evidence primarily so that it confirms the group's initial proposition, as well as the suppression of disconfirming evidence, i.e. the group conducts self-censorship (Janis, 1972). All of these symptoms are toxic to evidence-based decision making.

Now, it is important that groupthink is not how scientific consensus formation works, even though the consensus is described as an aggregate of what several experts, that is, a group in a specific field, agree upon. First, the measures to identify a scientific consensus (e.g. systematic review, surveys, network analyses) do not rely on a cohesive group but on research conducted by several independent groups around the globe that, in some cases, do not even know of each other's existence. Second, norms for methodological procedures are a particular strength of scientific research. However, other structural faults, dysfunctional norms and fraud within scientific communities can enable groupthink in research groups. For

example, the way scientists are incentivized, with high pressure to publish (Smaldino & McElreath, 2016) provides a “provocative context” (i.e. high stress from external threats) and thus a fertile ground for groupthink. This potential source of bias, among other issues, has triggered debates about how scientific work should be conducted and incentivized in the future (XXX).

Measures to counter symptoms of biased processes are already implemented in many research communities. For example, preregistration and open data are two measures that counter hypothesizing after results are known (i.e. HARKing), selective statistics (e.g. p-hacking) and only publishing significant results (i.e. file drawer problem) (Friese & Frankenbach, 2020; Murphy & Aguinis, 2019). All three are symptoms of a provocative context. Initial results suggest that preregistration strongly changes the percentage of published results that do not support the authors’ initial hypothesis. Estimates of “negative findings” from general literature are around 5-20% while registered reports provide negative findings in 55-66% of cases (Allen & Mehler, 2018). This suggests that preregistration counters the file drawer problem. However, current incentives for researchers to conduct open science and preregistration are still rare, and concerns about limiting creativity and higher costs (e.g., time required for preregistration) have led to some hesitation among researchers (Allen & Mehler, 2018; Moher et al., 2018). Proponents of open science in turn are addressing, and in some cases debunking, such concerns. An increasing number of freely available software

solutions are also helping to support open science practices, though it may be some time before the status quo changes (Nosek et al., 2018).

There are, however, other cases of consensus formation among some scientists that are expected to be much more biased than the previously mentioned procedures for assessing scientific consensus. When like-minded scientists unite to form a group and publish a statement about a specific proposition then this process is very likely prone to cohesion. During the COVID-19 pandemic, several medical doctors that questioned the effectiveness and safety of COVID-19 vaccination have teamed-up and published misleading statements. For example, in Austria 199 medical experts signed such a statement (Der Standard, 2021). Now while this number may be perceived as very high by laypeople, they only make up 0.4 % of medical doctors in Austria. Thus, while those statements mimic a scientific consensus they only prove the outsider position of this proposition if compared to a base rate. This is not to say that all statements from self-selected expert groups are misleading or necessarily result in groupthink, but the *process* of reaching such statements should be closely monitored to prevent dysfunctional teamwork. One way to improve the process is to conduct the selection of experts systematically and independently of their prior opinions. This is, for example, how the group of authors of the Debunking Handbook 2020 were selected (Lewandowsky et al., 2020).

In sum, scientific consensus formation is not a dogma but aims to provide an estimate of the current state of evidence for a specific

proposition. The consensus may be wrong and subject to change, but it does provide the best guidance on how to act given the current evidence. The process of scientific consensus formation is itself scientific, and thus is based on methods that lower levels of biases, like groupthink. However, the current incentivization of scientists provides an environment that fosters potentially biased decisions. Research communities and funders need to support measures that prevent closed mindedness by advocating for open science and by rethinking the incentive structures of scientific research.

## Scientific Community and the Public

During an emergency, people need timely advice to help them make evidence-based decisions so they can protect themselves and their communities from harm (Lundgren & McMakin, 2018). Therefore, the science community should reprioritise and coordinate their communication efforts towards those activities likely to have an effect upon those outcomes; that is, the most likely and severe risks that individual and organizational stakeholders of an issue may be exposed to, and the best mitigations for those risks. However, this kind of coordination is not a typical approach for many people who communicate science. A large component of science communication comprises individual scientists explaining their work, such as the findings of a newly published study. This means that as a community, science is often communicating in a disjointed, unorganized fashion, contrary to the approach used by practitioners of public relations.

To more strategically communicate scientific findings, the scientific community has much to learn from public relations done well (Borchelt & Nielsen, 2014). While the term public relations is often misunderstood, it is simply the planned and sustained organization of communication activities for fostering relationships, trust, and mutual benefit to stakeholders (Broom & Sha, 2013; CIPR, 2021). This allows public relations professionals to develop strategic communication programs in partnership with their stakeholders, to set and achieve measurable outcomes, like changes in behavior or policy. However, planning and organizing strategic communication programs is not a primary responsibility for many within the science community. Even those who have professional public communication responsibilities, such as press officers employed by the institutions of science (including universities and science associations), frequently operate according to the non-strategic press agentry or the public information models of public relations (Entradas et al., 2020; Metcalfe, 2019), where the focus is on generating media coverage or transmitting information in a one-way approach (Grunig et al., 1995), rather than developing trust or achieving behavioral or policy outcomes with their stakeholders.

Relying too heavily on this approach can leave scientists at a relative disadvantage in contested and complex communication landscapes, where people more practiced in communication strategy, such as politicians, media commentators and those with a direct commercial incentive, are better able to achieve their objectives. This can present unique challenges for

communicating science with the public during times of relative uncertainty, like a pandemic. The consequences are an unfortunate symptom of the frequently-criticized “information deficit” paradigm of science communication (Simis et al., 2016; Trench, 2006), a commonly used paradigm (Gascoigne et al., 2020) where people who communicate science seek to disseminate information, from those who have acquired knowledge to those who are regarded as having “deficits” in their knowledge, (Sturgis & Allum, 2004), without adequately understanding the needs of their audiences or engaging them for their input and participation (Besley & Nisbet, 2013).

While a deficit approach may be appropriate in some contexts, like during the initial stages of an emergency, it can lead to missed opportunities in engaging the public with science. “Public engagement has been more specifically defined as “seeking and facilitating the sharing and exchange of knowledge, perspectives, and preferences between or among groups who often have differences in expertise, power, and values” (National Academies of Sciences, Engineering, and Medicine, 2016, p. 131). Public engagement with stakeholders provides a mutually-beneficial mechanism for exchanging information about risks and barriers to mitigation, and for prioritizing those policy solutions that are most likely to be adopted (Voorberg et al., 2015). A clear example is that greater public engagement could have made public health advice more easily understood. Instead, much of the COVID-19 health advice is only accessible to those with high levels of education or health science literacy, hampering its effectiveness (Mac et al., 2021). Seeking and

responding to feedback from stakeholders could have remedied this in the drafting stage.

Moving from public engagement to participatory co-creation with stakeholders would have provided a yet stronger approach to maintaining frequent dialogue between stakeholders of an issue, who are invited to co-design “scientific endeavors” (Stocklmayer, 2013). The science community would be able to utilize the expertise of their community stakeholders as partners, to design and develop research of most benefit to them and to potentially reduce wasted money and effort (Fazey et al., 2013). Perhaps most crucially, co-creation could have provided opportunities to develop and maintain greater trust between the scientific community and audiences (Cvitanovic et al., 2021). This is a priority for future emergencies as a lack of trust in science has been identified as one of the predictors for why some people choose not to comply with risk-mitigating behaviors (Pagliaro et al., 2021). Therefore, ensuring the public trusts the empirical basis for any advice is important for building trust in its legitimacy.

Facilitating engagement, knowledge exchange, and co-creation between the science community, policymakers, and community stakeholders can be challenging. While it may be tempting to blame policymakers for not initiating engagement and co-creation with the science community and the public during the current pandemic, the science community should not wait for an invitation to do either. Instead, the science community should drive

the facilitation of these engagements with stakeholders and invite relevant policymakers to participate. Currently, there are no generally agreed guidelines for community engagement (Omoleke et al., 2021). Therefore finding the best format can be challenging as there are many different types, each with its potential benefits and detriments. This means care should be taken to find the most appropriate mechanism for each situation by considering the stakeholders' preferences (see Storksdieck et al., 2016, for a typology and comparison of commonly-used engagement mechanisms). This can be particularly challenging during an emergency. While it is possible to conduct dialogic communication with stakeholders via online platforms, including social media (Kent & Taylor, 2021), ideally, engagements should be conducted in-person to allow for greater relationship-building and dialogic knowledge sharing (Wilton et al., 2015). Engagement sessions should also be held recurrently, ideally composed of a panel of individual stakeholders and organizations in order to demonstrate the reflexive outcomes of previous engagements.

In conducting these engagements, the following principles adapted from the Clinical Translational Science Awards Consortium (2011) should be applied:

1. The purpose and goals should be explicit and clear.
2. All parties should seek to understand the norms, values, power structures and experiences of each under before the engagement.

3. Deliberate efforts should be made to develop trust and long-standing relationships.
4. All parties should respect the self-determination of the other parties, and a focus should be placed on community-driven actions.
5. All parties should be willing to persuade – and be persuaded by – the strength of each other's arguments.

There are some challenges to meeting these needs and utilizing opportunities. One key challenge is that science can be complex, dynamic, publicly controversial, contested by opposed agendas, and can include *mis*information and *dis*information. Compounding these problems is the fact that topics of science are often intellectually challenging (National Academies of Sciences, 2016), and may contradict people's pre-existing attitudes, beliefs and worldviews (National Academies of Sciences, 2017). Finally, facilitating engagements of this nature requires advanced communication skills, which may require professional facilitators or knowledge brokers. By using a participation and engagement approach instead of a deficit approach, we can develop science communications programs and conduct research in partnership with stakeholders to focus on the highest priority risks than any community faces, thus aligning joint efforts for achieving meaningful outcomes.

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